Finance Research Letters 57 (2023) 104209

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

The US banking crisis in 2023: Intraday attention and price variation of banks at risk

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ARTICLE INFO

Keywords:
Bank runs
Attention
Volatility models
Twitter
Silicon Valley Bank

ABSTRACT

After interest rate hikes by the FED, the market value of long-duration assets has declined, which in March of 2023 led to a distress of banks subject to a sudden increase in deposit withdrawals. First, Silicon Valley Bank and Signature Bank were subject to such runs and were taken over by the FDIC, while First Republic Bank by JPMorgan Chase in May of 2023. We date the crisis-period and show that increased Twitter-based attention is related to an increased price variation of banks at risk. Our results imply that during crisis periods, pricing can be improved by incorporating attention-based measures.

1. Introduction

A bank run occurs when a large number of depositors withdraw their funds from a bank due to concerns about its solvency or liquidity, leading to a liquidity crunch and, in some cases, a bank's failure (Diamond and Dybvig, 1983). On March 10, 2023, exactly this happened to one of the most prominent lenders in the start-up industry — Silicon Valley Bank (SVB), and Federal regulators had to step in to avoid a broader financial meltdown (Giang and Dang, 2023).

The bank run crisis in March 2023 could have far-reaching consequences, as it may not only affect individual banks but also have systemic implications for the broader financial system and later for its regulation. The crisis can trigger a domino effect, where the failure of one bank can lead to a contagion effect, leading to a chain of bank failures and systemic collapse. Jiang et al. (2023), for example, recently showed that if only half of the uninsured depositors decide to withdraw, almost 190 U.S. banks are at potential risk of impairment to even insured depositors, with potentially $300 billion of insured deposits at risk. They also emphasize that substantially more banks are at risk if the situation causes even small fire sales. Hence, bank runs can disrupt credit markets, impede economic growth, and damage public confidence in the financial system.

During times of crisis, investors and other market participants turn to the internet to either express their opinions about the ongoing situation or search for information about the phenomenon at hand. Hence, when forming short-term expectations about market movements, attention measures reflecting the situation in social media may contain information that can be used to improve predictions of future volatility. Several previous studies have shown that measuring sentiment and attention to an ongoing phenomenon and subsequently using those measures in volatility models can significantly improve our understanding of market behavior. The effects of attention and sentiment are amplified for unexpected and highly impactful events, whether it be the recent COVID-19 pandemic (Chen et al., 2020; Lyócsa et al., 2020a; Smales, 2021; Wang et al., 2021; Maghyereh and Abdoh, 2022),

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https://doi.org/10.1016/j.frl.2023.104209
Received 16 May 2023; Received in revised form 19 June 2023; Accepted 11 July 2023
Available online 18 July 2023

Brexit (Guidolin and Pedio, 2021), the Russian invasion of Ukraine (Lyócsa and Plíhal, 2022; Halousková et al., 2022), or even the Gamestop Short Squeeze episode (Lyócsa et al., 2022) where social medial provided a platform for a de-centralized coordination of small retail investors.

These studies, and many others (Aouadi et al., 2013; Vlastakis and Markellos, 2012; Hamid and Heiden, 2015; Dimpfl and Jank, 2016; Kristoufek, 2013, 2015; Urquhart, 2018; Xu et al., 2019; Audrino et al., 2020; Said and Slim, 2022) build on the limited attention hypothesis of Barber and Odean (2008). Though there is a vast amount of investment opportunities as well as market news, the attention of individual investors is a scarce resource (Kahneman, 1973). While some news are closely followed and monitored, other information is sometimes barely noticed. This implies that since the new information is incorporated into prices at the same rate. Andrei and Hasler (2015) show that the more attention a piece of information receives, the less time it takes to be incorporated into prices, which in turn might result in higher levels of volatility. Other authors (Da et al., 2022; Ballinari et al., 2022; Hirshleifer and Sheng, 2021) distinguish between the impacts of the attention of retail and institutional investors. The attention of institutional investors is considered to result in faster and more efficient price adjustments. On the other hand, if retail investors pay attention, they tend to either under or over-react (Barberis et al., 1998), causing noise trading and temporarily increasing price variation.

Based on the limited attention theory and the emergence of the empirical literature on the role of attention and sentiment in understanding market price behavior, we use high-frequency data to explore how Twitter-based attention relates to price fluctuations of banks at risk in the ongoing banking crisis. The approach allows us to date the crisis period and to examine whether the dynamics between the key variables experience structural changes. To the best of our knowledge, the present study is the first to examine the banking crisis from this perspective. Specifically, we study intraday price variation of six banks at risk: Silicon Valley Bank (SIVB), Silvergate Bank (SI), Signature Bank (SBNY), First Republic Bank Corporation (FRC), PacWest Bank (PACW) and Western Alliance Bancorporation (WAL). Using the attention towards the banks at risk, we date the crisis period to start at 15:30 on 8th of March and end at 12:00 on 21st of March 2023. While controlling for financial sector developments, other attention measures and intraday seasonality, we find robust evidence that increased attention leads higher price variation of the six banks at risk.

The paper is organized as follows. The next section describes the data sources and the construction of key variables of interest. The following section specifies our empirical strategy. The presentation of the results and a related discussion follows, while the final section concludes the paper and discusses a future research agenda.

2. Data and methodology

2.1. Measures of price-variation

We study the stock price variation of six banks that were subject to increased interest during the bank crisis of early 2023 (e.g., Masters et al., 2023; Reyes, 2023; Macheel, 2023), namely: Silicon Valley Bank (SIVB), Silvergate Bank (SI), Signature Bank (SBNY), First Republic Bank Corporation (FRC), PacWest Bank (PACW) and Western Alliance Bancorporation (WAL). We use 1 minute quoted stock price data retrieved from the FirstRate data provider. Given the sudden emergence of the crisis, our analysis is based on studying intraday price fluctuations. The 1 minute prices are aggregated into 30 minute measures of price fluctuations.[1] Given the 6.5 hour-long trading period, this results in 13 observations per day. Let $P_{t,i}$ denote the closing price at the $i = 0, 1, 2, \dots, n$ minute of a 30-minute trading window $t = 1, 2, \dots$. The annualized realized variance for the tth 30-minute trading window is given by:

$$RV_t = 252 \times \sum_{i=1}^{n} \left[100 \times (lnP_{t,i} - lnP_{t,i-1})\right]^2 \tag{1}$$

In our study, we control for the price fluctuations in the financial sector, where we use Eq. (1) to find the estimate of the 30-minute price variation of an equally-weighted portfolio comprised from ten financial institutions that had the largest weight in the S&P 500 financial sector market index.[2] The resulting realized measure is denoted as RV_t^{FIN}.

2.2. Measures of attention

We proxy investors' attention through their activities on the micro-blogging platform Twitter, using the Academic Twitter API access to the complete history of posts on the platform. Since the seminal work of Da et al. (2011), the probably most popular measure of investors' attention is Google search queries. Da et al. (2011) used Google trends that represent (a sample of) search frequency on Google for a specific search term or a phrase; an approach that was successful in modeling (e.g., Lyócsa et al., 2020a) or even predicting future price variations (e.g., Audrino et al., 2020). However, Da et al. (2011) employed excess attention over

[1] Note that the 1 minute prices can be aggregated into longer or shorter time-periods, although the possibilities are restricted in two ways. First, we need non-overlapping calendar sampling frequencies. For example, possible shorter time-periods could be 1 (no aggregation), 2, 3, 5, 6, 10, 13, 15, and 26 minutes, but these might be too noisy as they are a sum of less then 30 observations (see Eq. (1)), while longer time-periods could be only 39, 65, 78, 130 and 195 respectively or 390 which leads to daily sampling frequency. The second restriction is given by the attention measure, where we need a time-period with enough observations. As described later, we rely on tweets. We thus need enough relevant tweets for a given time period. For example, using a 1 minute time-periods would not give meaningful signal about the population's interest as it leads to many 0 tweets observations in the resulting attention measure.

[2] The highest weights as given in March 2023 were for: Berkshire Hathaway, JPMorgan Chase & Co., Bank of America Corporation, Wells Fargo & Company, Morgan Stanley, The Goldman Sachs Group, The Charles Schwab Corporation, S&P Global Inc., American Express Company, and the BlackRock.

the past time period and abnormal search volume intensity (ASVI). In a later study, Da et al. (2015) created the FEARS index that aggregates changes in ASVI across search terms that show the highest correlation between stock returns and search terms. This way one explicitly links (time-varying) relevant search terms with price movements. This approach is similar to that of Weiß et al. (2013) and Irresberger et al. (2015) who also create a correlation-based metric, where crisis-related search queries are correlated with stocks' ticker symbol search queries. Our approach to proxy investors' attention is more closely related to the works of Oliveira et al. (2017), Audrino et al. (2020), and Gjerstad et al. (2021), where a Twitter-based proxy for investors' attention is linked to stock price movements. Moreover, we do not use excessive (changes in) attention, nor correlation-based sentiment indices. Instead, we use logs of the aggregated volume of tweets, which is more useful for predicting volatility as opposed to predicting (abnormal) returns as in Da et al. (2011), Weiß et al. (2013), Irresberger et al. (2015), and Da et al. (2015). Apart from Google trends, alternative attention proxies exist, like newspaper articles about the topic of interest (Tetlock, 2007; Mao et al., 2011; Caporin and Poli, 2017; Brandt and Gao, 2019; Lyócsa et al., 2020b). However, we prefer Twitter for three reasons. First, the banking crisis started with the sudden withdrawal of deposits, and our proxy should thus capture the behavior of individuals (i.e., newspaper articles and broad media coverage might be written/directed by a small group of people). Second, Twitter is the largest micro-blogging social network in the US, and the Twitter-based proxy is thus likely to proxy for the attention of the whole country. Third, given the sudden onset of the crisis, our analysis requires high-frequency intra-day data that is, by design, available on Twitter.

We retrieve tweets written by English-speaking users published in the United States from January 3rd 2023 up to March 31st 2023. We create a list of search queries (in Table A.4) – phrases that would be included in the text of searched posts – in three broad categories:

1. Attention towards the stock market (WM) – 70 queries related to everyday trading on the stock market.
2. Attention towards crypto-currency markets (WC) – 18 queries associated with the crypto-currency market.
3. Attention to banks at risk (WB) – which consists of six subcategories corresponding to 126 queries related to the names of the six potentially affected banks, variations on their names, tickers, and phrases that include mentions of stock prices, insolvency, collapse, bankruptcy, and crash:
    - 25 queries for Silicon Valley Bank (SIVB),
    - 20 queries for Silvergate Bank (SI),
    - 18 queries for Signature Bank (SBNY),
    - 21 queries for First Republic Bank Corporation (FRC),
    - 21 queries for PacWest Bank (PACW),
    - 21 queries for Western Alliance Bancorporation (WAL).

Our key variable of interest is the attention towards the six banks at risk. Silicon Valley Bank had a highly concentrated business model that led to the sudden synchronized behavior from venture capital investors and technology firms '...who, fueled by social media, withdrew uninsured deposits in a coordinated manner at an unprecedented rate' (Barr, 2023, p. 4). Not only clients of the Silicon Valley Bank were concentrated in the Technology sector and innovative products in general, but also Silvergate Bank's customers were involved in fintech and cryptocurrencies. Clients of Signature Bank were also involved in crypto-currency markets (the bank allowed payments from and to cryptocurrencies). Therefore, apart from using the main attention measure, we also control for attention towards crypto-currency markets. To control for possible spill-over effects from attention towards cryptocurrency markets, our main specification uses an attention to cryptocurrency markets variable for all banks. Moreover, as part of the price variation might be due to the increased interest towards stock markets in general, we control for the general interest towards stock markets to account for potential other major market-relevant drivers of price fluctuations (e.g., monetary policy actions, regulatory actions), while assuming that actions that are specifically related to the banking crisis of 2023 lead to increased interest towards banks at risk and should be captured by our proxies of investors' attention to banks at risk.

Our procedure yielded 95 339 unique timestamped posts over 87 days. The attention variables are represented by the sum of relevant tweets posted within a given 30-minute window, starting from 00:00:00 EST. Let $W_{t,k}$ denote a tweet $k = 1, 2, \ldots$, that is posted within a given 30-minute time window $t = 1, 2, \ldots$. The three attention measures M_t (stock market), C_t (crypto-currency market), and B_t (banks at risk) are given by:

$$M_t = \sum_{k \in \mathrm{WM}} W_{t,k} \tag{2}$$

$$C_t = \sum_{k \in \mathrm{WC}} W_{t,k} \tag{3}$$

$$B_t = \sum_{k \in \{\mathrm{WB}\}} \frac{W_{t,k}}{6}, \tag{4}$$

where WM, WC and WB denotes tweets that are classified to be related to either the stock market (WM) topics, crypto-currency market (WC) topics or banks at risk (WB) topics.

2.3. Dating banking crisis: attention based approach

During the crisis period, attention towards banks at risk might play an elevated role in leading price fluctuations; inducing non-linearity in the attention and volatility relationship. However, the emergence of the US banking crisis in 2023 cannot be marked by a single specific event, which makes dating the crisis period difficult.

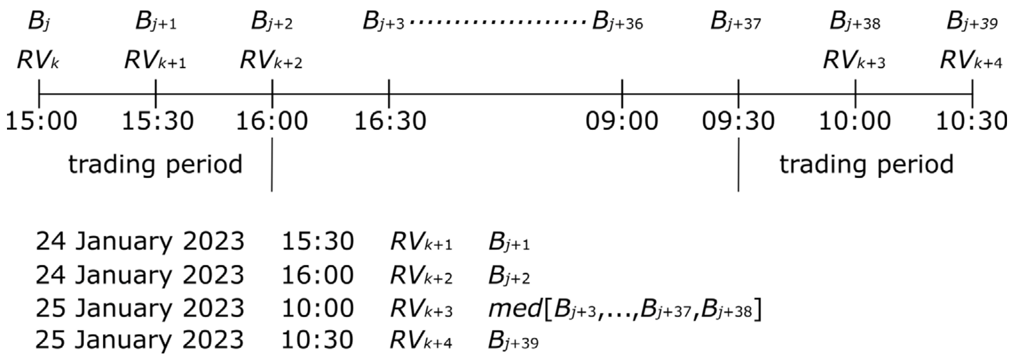

Fig. 1. Attention and price variation synchronization.

Given that the banking crisis received considerable media coverage in the U.S., the emergence of the crisis should be observed in the attention variable. Specifically, we use fluctuations in the banks at risk attention variable B_t, to determine the crisis period, as non-linear changes in attention should be accompanied by changes in the volatility process of the underlying variable.

We first filter the B_t using an ARMA(1,1) process that results in zero-mean residuals u_t that show no serial-correlation but significant auto-regressive conditional heteroscedasticity effects (as indicated by the Escanciano and Lobato (2009) test). We thus employ the κ_2 version of the Sansó et al. (2004) cumulative sum of squares test. Specifically, let $C(k) = \sum_{t=1}^{k} u_t^2$, with κ_2 statistics given by:

$$\kappa_2 = sup_k \left| \frac{G_k}{\sqrt{T}} \right| \tag{5}$$

where:

$$G_k = \frac{C_k - \frac{k}{T} C_T}{\sqrt{\hat{\omega}_4}} \tag{6}$$

Here, $\hat{\omega}_4$ is the auto-regressive conditional heteroscedasticity consistent estimate of the variance (e.g., Andrews, 1991) of the residual process u_t that we estimate using the Bartlett kernel weighting scheme and automatic bandwidth selection of Newey and West (1994). The test statistics are employed within the algorithm of Inclan and Tiao (1994) that can identify multiple breakpoints also accounting for potential masking effects.[3]

The resulting procedure led to two breaks, the first T_{b_1}, is identified on 8th of March 2023 at 15:30, while the second break, T_{b_2}, on 21th of March 2023 at 12:00. The resulting breaks are visualized in Fig. 2 and Fig. 3 and envelop the excessive attention during the onset of the crisis quite accurately.

2.4. Price variation and attention synchronization

We model 30-minute intraday price variation over the 6.5-hour trading windows.[4] However, Twitter does not sleep, and price-relevant attention might also be captured during the non-trading period. We have 30-minute attention estimates for the non-trading period as well, and we use the median attention as an outlier robust representation of non-trading period attention to substitute the attention for the first period of the trading window. Fig. 1 illustrates the synchronization between intraday price variation and attention in our dataset.

2.5. Empirical model specification

To estimate the role of attention on price-variation of bank's stocks, we estimate predictive auto-regressive models similar to the popular heterogeneous auto-regressive model of Corsi (2009). The models are able to capture the persistence of volatility while being straightforward to adjust with potential price-drivers. We employ a log specification to account for extreme price variation observed at the end of our sample period, since parameters are sensitive to such outlying observations within the OLS estimation

[3] The code in R with multiple alternative specifications is available upon request.

[4] The overnight price variation might be estimated (e.g., Hansen and Lunde, 2005), but compared to the realized variance, the estimate is less efficient, and as it covers a much longer time period, one might argue that the data-generating processes for intraday and overnight price variations differ. Moreover, a recent study by Lyócsa and Todorova (2020) presented evidence that on the US market, the stock's own overnight price variation had little effect on the next day's price variation.

Table 1
Characteristics of price fluctuation and attention measures.

		Mean	S.D.	Min.	Q1	Med.	Q3	Max.	$\rho(1)$	$\rho(14)$	KPSS	HEGY
Panel A: Price variation measures - realized volatility												
Silicon Valley Bank	RV_t^{SIVB}	4.79	1.11	2.27	4.07	4.54	5.26	10.32	0.60	0.45	0.02	16.3***
Silvergate Bank	RV_t^{SI}	7.29	1.24	4.59	6.32	7.23	8.06	12.21	0.73	0.62	0.25	23.7***
Signature Bank	RV_t^{SBNY}	4.93	1.10	3.14	4.19	4.66	5.40	10.73	0.62	0.53	0.04	14.2***
First Republic Bank	RV_t^{FRC}	5.00	2.18	2.24	3.44	4.08	6.10	12.02	0.92	0.87	0.38*	21.7***
PacWest Bankcorp	$RV_t^{PacWest}$	4.94	1.85	2.03	3.60	4.32	5.86	11.30	0.89	0.84	0.20	24.3***
Western Alliance Bankcorp	RV_t^{WAL}	5.16	1.91	2.47	3.80	4.51	6.06	12.78	0.88	0.84	0.21	20.0***
Bank industry	RV_t^{FIN}	2.93	1.01	1.10	2.20	2.66	3.43	7.27	0.62	0.70	0.06	20.3***
Panel B: Attention measures towards												
Crypto-curr. market	C_t	6.56	0.01	6.55	6.56	6.56	6.57	6.59	0.17	0.09	0.27	27.5***
Stock market	M_t	6.14	0.01	6.12	6.13	6.14	6.14	6.17	0.17	0.24	0.19	24.1***
Banks at risk	B_t	2.43	0.09	2.40	2.40	2.40	2.41	2.96	0.93	0.73	0.26	16.7***

Notes: S.D. denotes standard deviation, Q1 and Q3 are first and third quartiles respectively, $\rho(.)$ is the auto-correlation coefficient of a given order. Using the automatic Portmanteau test for serial correlation of Escanciano and Lobato's (2009) test with maximum lag corresponding to 14 observations, all variables show significant serial-correlation. KPSS presents the test statistics and significance of the (null) stationarity hypothesis of Kwiatkowski et al. (1992) with variance corrections as introduced by Sul et al. (2005, see Section 5), where *, ** and *** correspond to the usual 10%, 5%, and 1% significance level. HEGY reports the joint F-test of the seasonal unit-root hypothesis of Hylleberg et al. (1990) where given the 13 intra-day observations, we assumed a potential seasonality up to the last 14 observations.

framework. Moreover, the log-specification has a convenient elasticity interpretation. The baseline specification, estimated for each bank separately, is given as:

$$\begin{aligned} ln(RV_{t+1}) = \quad & \beta_0 + \beta_1 ln(RV_t) + \beta_2 ln(RV_{t:t-4}) + \\ & \beta_3 ln(RV_t^{FIN}) + \beta_4 ln(C_t) + \beta_5 ln(M_t) + \beta_6 ln(B_t) + \\ & \sum_{s=1}^{12} \gamma_i S_{t,s} + \epsilon_t \end{aligned} \tag{7}$$

Here, the $RV_{t:t-4}$ denotes the average realized variance over the last five observations. As intraday price variation is known to have seasonal effects, we control for seasonality using $S_{t,i}$ indicator variables.

Accounting for the structural breaks in attention identified in Section 2.3 leads to our two-regime[5] bank-level specification:

$$\begin{aligned} ln(RV_{t+1}) = \quad & \beta_0 + \beta_1 ln(RV_t) + \beta_2 ln(RV_{t:t-4}) + \\ & I(t < T_{b_1} \wedge t > T_{b_2}) \times \left[\beta_3 ln(RV_t^{FIN}) + \beta_4 ln(C_t) + \beta_5 ln(M_t) + \beta_6 ln(B_t)\right] + \\ & I(t \geq T_{b_1} \wedge t \leq T_{b_2}) \times \left[\beta_7 ln(RV_t^{FIN}) + \beta_8 ln(C_t) + \beta_9 ln(M_t) + \beta_{10} ln(B_t)\right] + \\ & \sum_{i=1}^{12} \gamma_i S_{t,i} + \epsilon_t \end{aligned} \tag{8}$$

Here, the $I(.)$ is an indicator function returning a value of 1 if the given observation belongs to the time period outside of the elevated attention regime and 0 otherwise. The effect of RV_t^{FIN}, C_t, M_t, and B_t is thus estimated separately for the two regimes.

We report the two-regime specification only if it led to a superior fit as indicated via the model confidence set (MCS)[6] of Hansen et al. (2011). The tables report the p-value corresponding to the equal predictive ability hypothesis.

3. Results

3.1. Exploratory observations

Before we proceed with our main analysis, we confirm stylized facts of realized price variation and attention measures. In Table 1, we report results from the log-transformed measures as they appear in our models. We observe that all price-variation measures are: (i) highly persistent with first-order auto-correlation coefficients ranging from 0.60 (Silicon Valley) up to 0.92 (First Republic), (ii) show intraday seasonality as the same trading window of the previous day (lag 14) shows a persistence ranging from 0.45 (Silicon Valley) to 0.87 (First Republic) and (iii) right-skewness as indicated by quantiles of the volatility distributions.

The persistence, distributional properties, and intraday seasonality of price-variation measures are also visible in Fig. 2. The end of our sample can be characterized by excessive price variation that appears to coincide with the beginning of the identified

[5] The two breaks lead to three regimes. As opposed to the baseline model, we are interested in the potential effects found during the elevated attention period, which leads to the two-regime specification.

[6] The procedure is often used in the volatility forecasting literature to evaluate out-of-sample forecasts, but as Hansen and Lunde (2005, Section 6.2) shows, the approach can be used to select between competing models in an in-sample framework. For that purpose, our loss function was simply the squared residuals from the baseline and two-regime model specifications. We used the T_{MAX} test statistics.

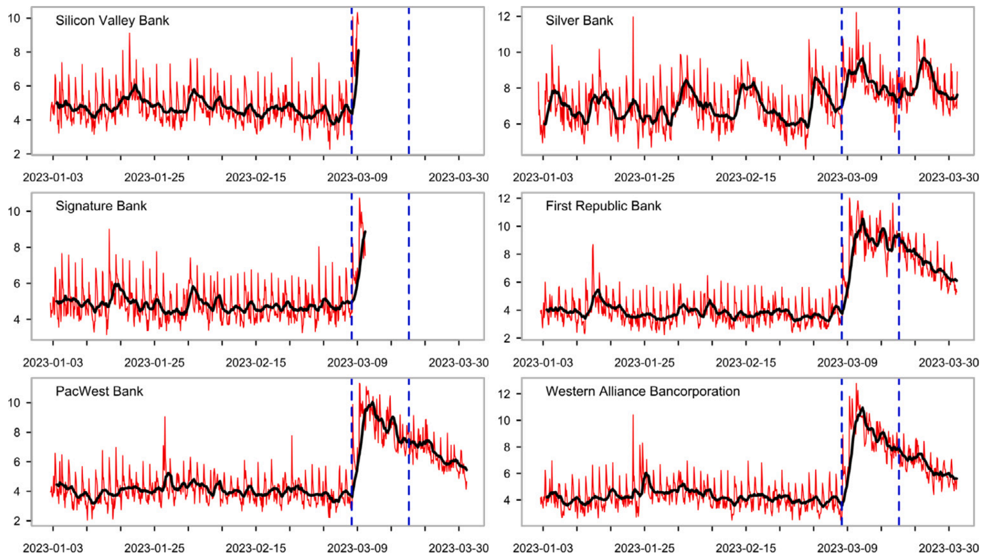

Fig. 2. Price variation of banks at risk.
Notes: The red-line corresponds to the 30-minute realized price-variation estimated from 1-minute quoted prices. The black lines are 13 observation rolling means aligned to the right. Vertical blue dashed lines highlight the elevated attention to banks at risk regime, which starts on 8th of March 2023 at 15:30 and ends on 21th of March 2023 at 12:00.

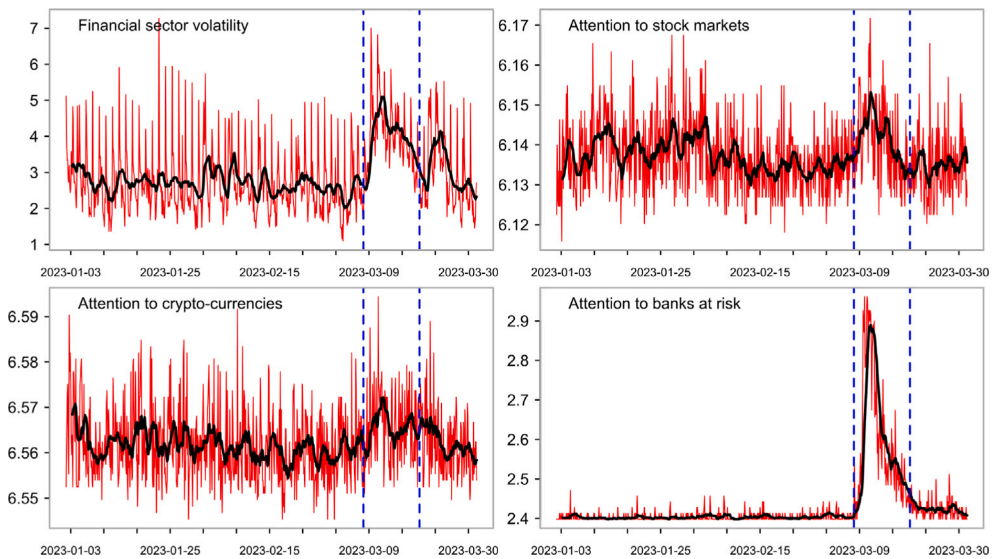

Fig. 3. Attention measures and industry-wide price variation.
Notes: The red line corresponds to the 30-minute realized price-variation estimated from 1-minute quoted prices (upper left plot) while remaining plots show 30-minute attention measure. The black lines are 13 observation rolling means aligned to the right. Vertical blue dashed lines highlight the elevated attention to banks at risk regime, which starts on 8th of March 2023 at 15:30 and ends on 21th of March 2023 at 12:00.

elevated attention period (blue dashed lines). The shorter sample period for Silicon Valley Bank and that of Signature Bank[7] show that the overlap between price variation measures and the elevated attention period is much shorter.

One can expect that as topics of interest are publicly debated, the resulting attention measures will be persistent (e.g., Bucy et al., 2020; Zhang et al., 2019; Lyócsa et al., 2020a; Lyócsa and Plíhal, 2022). The results in Table 1 show that attention to banks at risk (B_t) is highly persistent and also shows seasonality. In contrast, attention to crypto-currency markets (C_t) and stock markets (M_t) has much lower persistence, but we can also observe higher average interest and less fluctuation over our sample period.

[7] Where trading was halted until 28th of March 2023.

Table 2
Intraday price variation model with attention measures: The case of Silicon Valley Bank, Silvergate Bank, and Signature Bank.

		Silicon Valley Bank	Silvergate Bank	Signature Bank
Constant		−16.324	5.147	−12.965
Panel A: Price fluctuations				
Bank's 1-period lag volat.	RV_{t-1}	**0.433*****	**0.506*****	**0.460*****
Bank's 5-period average lagged volat.	RV_{t-5}	**0.283*****	**0.360*****	**0.306*****
Financial sector 1-period lag volat.	RV_{t-1}^{FIN}	**0.090****	0.026	0.025
Panel B: Attention measures towards				
Crypto-currency market	C_{t-1}	0.609	−0.994	0.025
Stock market	M_{t-1}	2.409	0.463	1.823
Banks at risk	B_{t-1}	0.402	**0.585****	**2.098****
Panel C: Period C of elevated attention from 15:30 8th March to 11:00 17th March				
Financial sector 1-period lag volat.	$I(.) \times RV_{t-1}^{FIN}$	0.101		
Attention to crypto-currency market	$I(.) \times C_{t-1}$	−7.980		
Attention to stock market	$I(.) \times M_{t-1}$	4.311		
Attention to banks at risk	$I(.) \times B_{t-1}$	**19.076****		
Panel D: Control variables				
Intraday seasonality dummies		Yes	Yes	Yes
Panel E: Model characteristics				
R^2		0.799	0.765	0.798
$adj.R^2$		0.791	0.759	0.792
ρ(max)		0.080	0.082	0.133
EL test (p-value)		0.587	0.827	0.002
MCS test (p-value)		0.007	0.062	0.127
Block length		13	39	23
#obs.		594	806	606
Sample period – beginning		Jan 3rd 2023	Jan 3rd 2023	Jan 3rd 2023
– end		March 9th 2023	March 31st 2023	March 10th 2023

Notes: Uncertainty of the estimated coefficients is based on the stationary-bootstrap procedure of Politis and Romano (1994) with 2000 bootstrapped samples, where the random block length are drawn from a geometric distribution with expected value equal estimated via the automatic block length procedure of Politis and White (2004) and Patton et al. (2009). The estimated block-lengths are denoted as Block length in the table. The blocks of data should capture the time-series properties of the variables in Panel A and B. The 10%, 5% and 1% significant coefficients are denoted as *, **, and ***, respectively. The $\rho(max)$ denotes the largest auto-correlation of residuals found up to lag 14. EL is the p-value of the Escanciano and Lobato (2009) test of no-serial correlation up to lag 14. The MCS test denotes the p-value of the equal predictive ability test of Hansen and Lunde (2005) comparing the baseline model with the two-regime model. The alternative hypothesis being that the two-regime model has a superior fit against the baseline model.

Fig. 3 shows how attention towards banks at risk increased abruptly on 8th of March 2023, and the elevated attention lasted almost two weeks until 21st of March 2023. During that period, we can also observe elevated price fluctuation in the financial sector, but also in the attention towards crypto-currency markets and towards stock markets in general. All factors that we control for in the modeling.

3.2. Models of price variation

Tables 2 and 3 show the estimates of the volatility models. As is usual in the volatility modeling literature, the lagged price fluctuations capture most of the volatility persistence. The coefficients are positive and significant across all banks. Despite the observed increased price variation of the financial sector, crypto-currency, and stock market attention (see Fig. 3), we find a positive and significant relationship only for the financial sector price variation in the Silicon Valley Bank model. Overall, the fit of the models is always above 76.5% (Silvergate Bank), and the residuals show only mild levels of persistence left up to lag 14 (covering the intraday seasonality of the data).

Note that we report results from the two-regime model specification only if the null hypothesis of equal predictive ability between the baseline and two-regime models is rejected. This happened only once, for the Silicon Valley Bank model. This is quite intriguing given that trading had been halted on 9th of March, just before the bank was taken over by the Federal Deposit Insurance Corporation (FDIC). Thus there are only 15 observations corresponding to the elevated attention regime. Yet, the MCS test has favored the two-regime model. The attention to banks at risk variables is positive and significant only during this short period of time, but the effect size is extreme. The 19.076 corresponds to an effect, where 1% increase in attention (B_t) leads to a 19.076% increase in realized variance (RV_t).[8] In the Signature Bank model, another institution that FDIC took over in March, we also estimate an overall positive, significant, and considerable effect of 2.098. It seems that despite the short-lived trading of the two stocks during the elevated attention regime, the increased attention was a significant predictor of intraday price variation.

[8] The coefficient loaded at the attention to banks at risk is positive and significant at the 10% level while having a considerable effect of 9.782 for the baseline model.

Table 3
Intraday price variation models with attention measures: The case of First Republic Bank, Pacific West Bank, and Western Bank.

		First Rep.	PACW	Western
Constant		**−43.924**[**]	5.383	11.326
Panel A: Price fluctuations				
Bank's 1-period lag volat.	RV_{t-1}	**0.643**[***]	**0.578**[***]	**0.578**[***]
Bank's 5-period average lagged volat.	RV_{t-5}	**0.304**[***]	**0.355**[***]	**0.355**[***]
Financial sector 1-period lag volat.	RV_{t-1}^{FIN}	0.032	−0.025	0.006
Panel B: Attention measures towards				
Crypto-currency market	C_{t-1}	**6.620**[**]	−2.320	**−2.702**[*]
Stock market	M_{t-1}	0.195	1.553	0.841
Banks at risk	B_{t-1}	**0.572**[**]	**1.068**[**]	**1.517**[***]
Panel C: Control variables				
Intraday seasonality dummies		Yes	Yes	Yes
Panel D: Model characteristics				
R^2		0.923	0.895	0.897
$adj.R^2$		0.921	0.892	0.894
ρ(max)		−0.103	0.079	0.139
EL test (p-value)		0.924	0.691	0.828
MCS test (p-value)		0.219	0.209	0.250
Block length		42	42	42
#obs.		594	806	606
Sample period – beginning		Jan 3rd 2023	Jan 3rd 2023	Jan 3rd 2023
– end		March 9th 2023	March 31st 2023	March 10th 2023

Notes: Uncertainty of the estimated coefficients is based on the stationary-bootstrap procedure of Politis and Romano (1994) where the random block length are drawn from a geometric distribution with expected value equal estimated via the automatic block length procedure of Politis and White (2004) and Patton et al. (2009). The estimated block-lengths are denoted as Block length in the table. The blocks of data should capture the time-series properties of the variables in Panel A and B. The 10%, 5% and 1% significant coefficients are denoted as *, **, and ***, respectively. The $\rho(max)$ denotes the largest auto-correlation of residuals found up to lag 14. EL is the p-value of the Escanciano and Lobato (2009) test of no-serial correlation up to lag 14. The MCS test denotes the p-value of the equal predictive ability test of Hansen and Lunde (2005) comparing the baseline model with the two-regime model. The alternative hypothesis being that the two-regime model has a superior fit against the baseline model.

As the two banks were bankrupt, the Federal Reserve created 'The Bank Term Funding Program' to build-up confidence. The program allows banks at risk to sell their assets at the full-face amount rather than market value. Moreover, the FED made lending through the discount window more accessible. On March 22, FED raised the baseline interest rate only by 25 basis points, while J. Powell mitigated the expectation for future rate hikes, and in their statement, the FOMC reassured the markets that 'The U.S. banking system is sound and resilient.' (FOMC, 2023). All these actions suggest that financial institutions were fragile and suspect of sudden deposit withdrawals. Our analysis shows that for all the remaining financial institutions in our sample, attention to banks at risk was a significant predictor as well. Although the effects were smaller than for the banks that went bankrupt at the early stages of the crisis, they were not negligible. The smallest (and significant) effects of 0.572 and 0.585 are estimated for First Republic and Silvergate Banks. For the PacWest and Western Alliance, the effects are larger at 1.068 and 1.517, respectively, suggesting that investors might have been more sensitive to the development of the two financial institutions. These results are in line with several recent studies (e.g., Lyócsa and Plíhal, 2022; Halousková et al., 2022) that also show that during crisis periods, attention can play a significant role in modeling price variation. Moreover, the effect of the attention is non-linear, given that we use log–log specifications and the estimated elasticity of price-variation to attention was close to or above 1.

3.3. Alternative modeling choices: robustness checks

The observed effects might be driven by intraday seasonality, which we account for in our specifications. The indicator variable capturing the first 30 minutes of the trading period also controls for overnight discontinuities of the price-variation process. With respect to the estimate of the attention for the first 30 minutes of the trading window, we employed the median attention level over the 30 minute sampling period of the non-trading period (see Fig. 1). We have re-run the analysis with the average or maximum attention levels instead. The estimated effects were qualitatively similar: all attention elasticity coefficients are positive and significant, except for First Republic, while the effect sizes are comparable.[9]

In our main specifications, we control for the level of past price variation using one and five-period average volatilities. Given the different persistence characteristics of other volatility components, we considered several alternative specifications. First, instead of the overall price variation measures, we employed one and five-period average continuous and jump components as estimated

[9] Using the mean, the elasticity for the same specifications as reported in Tables 2 and 3 are 19.30, 0.587, 2.105, 0.578, 1.068 and 1.517 for SIVB, SI, SBNY, FRC, PACW, and WAL. With maximum, the same coefficients are 18.716, 0.336, 2.400, 0.761, 1.038, and 1.237.

by Andersen et al. (2012). Second, we used positive and negative semi-variances (see Patton and Sheppard, 2015). In both cases, we observe qualitatively similar estimates of the attention effect.[10]

Continuous and jump components, as well as positive and negative semi-variances, are parts of the overall price variation. We thus study whether the previously identified effect can be isolated for a specific component of the overall price variation measure. We predict continuous and jump components while controlling for past continuous and jump components, as described in the previous paragraph. We find that attention is consistently positively associated with the future continuous component of the price variation only.

During crisis periods, negative auto-correlation of returns are to be expected (e.g., Longstaff (2010) during the sub-prime crisis or Lyócsa and Molnár (2020) during the onset of the COVID pandemic), thus positive and negative expectations might be altering and attention might be associated with positive as well as negative semi-variances alike. We also predict positive and negative semi-variances while controlling for past semi-variances. The size of the effect is always positive, so in general, attention tends to increase price-variation, but the effect tends to be stronger with price-decreasing price variation, which we found was the case for all banks except the Western Alliance.[11]

Not all banks in our sample had strong ties to the cryptocurrency markets; thus one might argue that attention towards cryptocurrency markets should not be included in all specifications. We, therefore, tested specifications without cryptocurrency attention, but the results remained very similar[12]

4. Conclusion

The banking crisis in 2023 emerged suddenly, arising from risks that were not subject to tighter regulation, e.g., industry-concentrated customer base, a larger proportion of uninsured deposits, and portfolio of low credit risk bonds with high market risk measures. In such an environment, the power of social media may act as a trigger that exposes the fragility of such banks.

A potential run on a bank should be captured by increased attention towards banks at risk. This, in turn, should also trigger market behavior that manifests into increased price variation. We study whether the volume of tweets, as a proxy for investors' attention, related to the six banks at risk led to increased price variation. Our analysis is based on the 30-minute intraday price variation of six banks: Silicon Valley Bank (SIVB), Silvergate Bank (SI), Signature Bank (SBNY), First Republic Bank Corporation (FRC), PacWest Bank (PACW) and Western Alliance Bancorporation (WAL), over the sample period from January 3, 2023, until March 31, 2023. We have several interesting results. First, we find that attention to banks at risk is highly persistent, which suggests that if there is an effect of attention on the stock prices, it will not suddenly disperse. Second, using the attention to banks at risk and the κ_2 test of Sansó et al. (2004), we dated the beginning of the crisis period to start from $15:30$ on March 8, 2023, while the elevated attention ended at $12:00$ on March 21, 2023. During this period, two banks were taken over by FDIC, and the attention was the highest. Third, we found that during our sample period price-variation in the financial sector, attention to crypto-currency markets and the stock market in general played little role in the intraday-price variation of the six banks at risk. This is an interesting finding as it shows that the crisis is likely an isolated one, not spilled over from the crypto-currency market, the financial sector as a whole, or the stock market in general. Fourth, our key result is that attention to banks at risk is positively related to future intraday price variation. The effect is found for all six banks. Just before the bankruptcy, the effect for the Silicon Valley Bank was non-linear with an estimated elasticity of 19.076, i.e., a 1% increase in attention led to a 19.076% increase in price-variation during the onset of the crisis period. Fifth, we found that the effect is robust across different model specifications and we documented that the effect of the attention to banks can be further isolated to reside in the continuous part of the price variation (not the jump component) and the negative semi-variances (not positive semi-variances).

Our results imply that during sudden crisis periods, financial risk-mitigating strategies might be improved by employing attention measures from social media. The attention measures can for example be used to build early warning indicators. Our research also suggests some future research paths of interest as the accuracy of the attention measures might be likely improved if interacted with measures of negative sentiment.

CRediT authorship contribution statement

Štefan Lyócsa: Conceptualization, Methodology, Investigation, Writing – original draft. **Martina Halousková:** Data curation, Software, Visualization, Writing – original draft. **Erik Haugom:** Conceptualization, Validation, Writing – original draft.

Data availability

Data will be made available on request.

[10] For the continuous and jump component specification, the estimates are 19.69, 0.533, 2.102, 0.776, 1.119, 1.402 for SIVB, SI, SBNY, FRC, PACW, and WAL, while for the semi-variance model specification, the estimates are 19.254, 0.687, 1.887, 0.800, 1.012, and 2.100.

[11] Predicting the positive (negative) semi-variance the effects were 17.607 (20.070), 0.314 (0.895), 2.124 (2.119), 0.402 (0.723), 0.940 (0.949), 2.127 (0.147) for SVIB, SI, SBNY, FRC, PACW and WAL.

[12] he estimated parameters for attention towards banks at risk were $18.741, 0.576, 2.098, 0.621, 1.055, 1.509$ for SVIB, SI, SBNY, FRC, PACW and WAL.

Acknowledgments

This research was supported by the Czech Science Foundation (GACR), nr. 20-11769S.

Appendix

See Table A.4.

Table A.4
Twitter search queries by category.

Category	Keywords
Stock market	Stock Market, Stocks, Bullish, Bearish, S&P 500, Wall Street, financial markets, wall street journal, nasdaq, nyse, earnings, per share, quarterly report, earnings, call, price to earnings, price to book, market capitalization, market price, financial times, VIX, market volatility, gold, price, t bill, treasury bill, treasury bond, 401(k), Asset Allocation, pension funds, trading volume, bear market, bull market, day, trading, technical analysis, dividend yield, futures contract, finance google, finance yahoo, marketwatch, hedge fund, market, index, mutual funds, economic recession, stop order, limit order, trading strategy, yield curve, option contract, stock symbol, market order, penny stocks, market bubble, financial crisis, market liquidity, The Motley Fool, Bloomberg.com, seeking, alpha, market downturn, volatile market, fidelity investments, etrade, ameritrade, Implied volatility, FTSE 100, Nikkei, Hang Seng Index, EURO Stoxx 50, Russell 2000, European Central Bank, EUR/USD, Eurodollar, Robinhood
Crypto-currency market	crypto, cryptocurrency, Bitcoin, BTC, ETH, blockchain, ethereum, tether, XRP, Ripple, coinbase, finance, cryptonews, altcoins, altcoin, stablecoin, stablecoins, cryptocurrencies
SVB	SVB, Silicon Valley Bank, SiliconValleyBank, SVB bank, SIVB, $SIVB, SVB Financial, SVB Financial Group, Silicon Valley Bank stock, Silicon Valley Bank stock price, SiliconValleyBank stock, SiliconValleyBank stock price, SVB stock, SVB stock price, SVBCollapse, SVB collapse, SIVB collapse, SVB insolvent, SIVB insolvent, SVB bankrupt, SIVB bankrupt, SVB bankruptcy, SIVB bankruptcy, SVB Crash, SIVB Crash
Silver Gate	Silver Gate, SilverGate, Silvergate Capital, $SI, Silver Gate stock, Silver Gate stock price, silvergate stock, silvergate stock price, SI stock, SI stock price, Silver Gate collapse, SI collapse, Silver Gate insolvent, SI insolvent, Silver Gate bankrupt, SI bankrupt, Silver Gate bankruptcy, SI bankruptcy, Silver Gate Crash, SI Crash
Signature Bank	Signature Bank, SignatureBank, $SBNY, SBNY, signature bank stock, signature bank stock price, SBNY stock, SBNY stock price, Signature Bank collapse, SBNY collapse, Signature Bank insolvent, SBNY insolvent, Signature Bank bankrupt, SBNY bankrupt, Signature Bank bankruptcy, SBNY bankruptcy, Signature Bank Crash, SBNY Crash
First Republic Bank	First Republic Bank, FirstRepublicBank, First Republic, $FRC, FRC, first republic bank stock, first republic bank stock price, first republic stock, first republic stock price, FRC stock, FRC stock price, first republic bank collapse, FRC collapse, first republic bank insolvent, FRC insolvent, first republic bank bankrupt, FRC bankrupt, first republic bank bankruptcy, FRC bankruptcy, first republic bank crash, FRC crash
PacWest Bancorp	PacWest Bancorp, PacWestBancorp, PacWest, $PACW, PACW, PacWest Bancorp stock, PacWest Bancorp stock price, PacWest stock, PacWest stock price, PACW stock, PACW stock price, PacWest collapse, PACW collapse, PacWest insolvent, PACW insolvent, PacWest bankrupt, PACW bankrupt, PacWest bankruptcy, PACW bankruptcy, PacWest crash, PACW crash
Western Alliance Bancorp	western alliance bancorp, Western Alliance Bancorporation, Western Alliance, western alliance bank, $WAL, western alliance bancorp stock, western alliance bancorp stock price, western alliance stock, western alliance stock price, WAL stock, WAL stock price, western alliance collapse, WAL collapse, western alliance insolvent, WAL insolvent, western alliance bankrupt, WAL bankrupt, western alliance bankruptcy, WAL bankruptcy, western alliance crash, WAL crash

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